Using First- and Second-Order Variograms for Characterizing Landscape Spatial Structures From Remote Sensing Imagery

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Abstract—**The spatial structures displayed by remote sensing imagery are essential information characterizing the nature and the scale of spatial variation of Earth surface processes. This paper provides a new approach to characterize the spatial structures within remote sensing imagery using stochastic models and geostatistic metrics. Up to now, the second-order variogram has been widely used to describe the spatial variations within an image. In this paper, we demonstrate its limitation to discriminate distinct image spatial structures. We introduce a different geostatistic metric, the first-order variogram, which used in combination with the second-order variogram, will prove its efficiency to describe the image spatial structures. We then develop a method based on the simultaneous use of both first- and second-order variogram metrics to model the image spatial structures as the weighted linear combination of two stochastic models: a Poisson line mosaic model and a multi-Gaussian model. The image spatial structures are characterized by the variance weight and the variogram range related to each model. This method is applied to several SPOT-HRV Normalized Difference Vegetation Index (NDVI) images from the VALERI database in order to characterize the nature of the processes structuring different types of landscape. The mosaic model is an indicator of strong NDVI discontinuities within the image mainly generated by anthropogenic processes such as the mosaic pattern of crop sites. The multi-Gaussian model shows evidence of diffuse and continuous variation of NDVI generally engendered by ecological and environmental processes such as the fuzzy pattern observed over forest and natural vegetation sites.**

Index Terms—**First-order variogram, landscape, multi-Gaussian model, normalized difference vegetation index (NDVI), Poisson line mosaic model, second-order variogram, spatial structure, stochastic simulation.**

I. Introduction

THE MONITORING of Earth surface dynamic processes such as primary production or carbon and water fluxes requires observations of the Earth surface properties at the proper spatial and temporal scales. Remote sensing data are particularly appropriate to describe surface processes since they provide continuous and frequent spatial estimates of key Earth surface variables [1]. Contrary to *in situ* data, remote sensing observations may exhibit the spatial heterogeneity of the retrieved surface property. This information helps characterizing the nature of the processes structuring the landscape [2], identifying their scale of spatial variation [3]–[6] and thus improving their representation in land surface models [7]–[9]. In addition, quantifying the surface spatial heterogeneity from remote sensing data are required to correct the bias associated with nonlinear estimation of land surface variables over heterogeneous pixels [10], [11] and for the disaggregation of coarse spatial resolution images to retrieve the surface property of objects smaller than the pixel size [9], [12], [13]. Appropriate methods must thus be established to extract and efficiently exploit the spatial heterogeneity information contained in remote sensing image.

Garrigues *et al.* [14] define the spatial heterogeneity of a surface property measured from remote sensing sensor through two components.

1) The spatial variability of the surface property over the observed scene as measured by the variance of the image.
2) The spatial structures: they are defined in this paper as patches or objects (e.g., agricultural fields, vegetation patches,...) that repeat themselves independently within the observed scene at a characteristic length scale (i.e., spatial scale) which represents the extent of the spatial structure. They can be viewed as the typical correlation area (i.e., the typical area of influence) of the surface property. Spatial structures within remotely sensed images are identifiable in that their spectral properties are more homogeneous within them than between them and other scene elements [15]. Data are often distributed into independent sets of spatial structures, related to different length scales and spatial variability, being overlaid in the same region.

This paper focuses specifically on the characterization of the spatial structures observed within remote sensing images. These spatial structures are specific to the measured surface property. The Normalized Difference Vegetation Index (NDVI) computed from red and near infrared reflectances [16] is the "state" variable used in this paper to describe the spatial structures of the landscape vegetation cover.

The characterization of the image spatial structures depends both on the geographic extent of the observed scene and on

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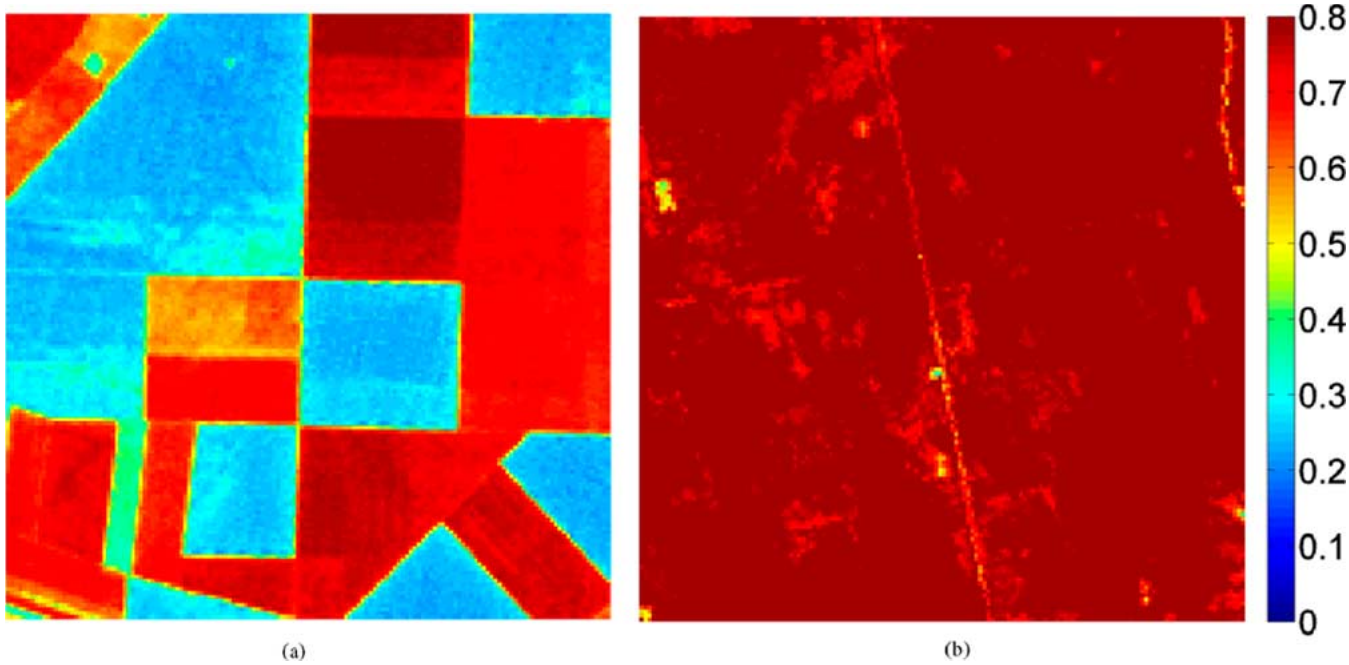

Fig. 1. Examples of landscape spatial structures characterized from high spatial resolution NDVI images (SPOT-HRV sensor at 20-m spatial resolution). (a) Cropland associated with mosaic spatial structure of the fields. (b) Forest site associated with fuzzy spatial structure of the vegetation cover.

the size of the spatial support on which the signal is integrated [17]–[20]. A scene must be large enough compared to the extent of the spatial structures to encompass their spatial variability [14]. In this paper, the spatial structures of vegetation cover are analyzed at the landscape level defined as an area of few square kilometers (9 to 50 km^2). Garrigues *et al.* [14] show that this area is large enough to resolve the spatial variability of most landscape spatial structures. The size of the spatial support of remote sensing data involves two characteristics of the sensor: the ground sampling distance (GSD) and the point spread function (PSF). The GSD is the size of the ground projection of the sensor instantaneous field of view which is approximated by the pixel of the image. Its value at nadir defines the nominal pixel size of the image. In addition, the sensor system applies a low pass spatial filter to the radiometric signal, characterized by the PSF. The width of the PSF affects the size of the actual spatial support of the data which may be larger than the GSD. The combination of PSF and GSD determines the minimum size of the objects detected by the sensor. A surface spatial structure cannot be captured by the data when the size of the spatial support of the data is larger than the extent of the spatial structure [14]. The size of the spatial support of high spatial resolution data (e.g., Satellite Pour l' Observation de la Terre High Resolution Visible (SPOT-HRV), GSD $= 20$ m) is small enough to resolve the spatial structures of most landscapes [14]. It is also large enough to limit the noise generated by spatial structures at very small length scales that may hamper the proper characterization of the spatial structures of vegetation cover at the landscape level [14].

In addition, the shape and the variability associated with the spatial structures of vegetation cover depend on the type of landscape [14]. Cropland spatial structures are generally characterized by a mosaic pattern and generate large NDVI spatial variability [Fig. 1(a)]. Spatial structures of natural vegetation and forest have fuzzier pattern and are associated with smaller NDVI variability than agricultural field structures [Fig. 1(b)].

Several metrics can be used to describe the spatial variations within an image. Julesz [21] underlines that one point statistics (e.g., image histogram) are not efficient to describe image spatial variations since they do not account for spatial correlations between data. Two point statistics which describe the spatial relationships between data are thus more appropriate [21]–[23]. Garrigues *et al.* [14] provide a comparison of some two point statistics metrics used to explore the spatial variations within an image which includes Haralick indexes [23], fractal and multifractal analysis [24]–[28], Fourier transform [29], [30], wavelet transform [6], [25], [30], and second-order variogram [15], [31]–[37]. Among these metrics, it is shown in Garrigues *et al.* [14] that modeling the second-order variogram of high spatial resolution NDVI image is an efficient method to characterize the spatial structures of the landscape. In their approach, variogram parameters are related to the length scales and the spatial variability associated with each set of spatial structures being overlaid in the image.

However, Gagalowicz [22] shows that the information provided by the second-order variogram is not always sufficient to discriminate different types of spatial structure. This fact is also illustrated in Chilès and Delfiner [32] in which it is shown that several models of random functions can have exactly the same theoretical second-order variogram. In this paper, we propose to use another geostatistic tool, the first-order variogram which, together with second-order variogram, will prove to be powerful to describe the image spatial structure. Up to now, the first-order variogram has never been applied to remote sensing imagery. In addition, no studies have been specifically focusing on modeling the characteristics of the image spatial structures such as their size and shape in order to characterize the underlying processes structuring the landscape.